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NEURAL MODELS OF MOTION PERCEPTION

September 1, 1992—August 31, 1995

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ABSTRACT

Six research projects supported by this grant during the final year have resulted in one published book chapter, two refereed articles in press, three articles under review, and one refereed conference publication. Areas of research included design and simulation of network architectures for: (1) motion perception; (2) brightness perception; (3) spatial pooling and perceptual framing by synchronized cortical dynamics; (4) binocular disparity processing; (5) synthetic aperture radar processing by a multiple scale neural system for boundary and surface representation; and (6) perception of lightness in 3-D curved objects.

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SEPTEMBER 1, 1992—AUGUST 31, 1995

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RESEARCH SUMMARIES

1. Motion Perception [Articles 3 and 4]

How is the perceived direction of motion of a target affected by the motion of multiple surrounding regions? Observers viewed displays consisting of three nested regions, a circular target region surrounded by two concentric annuli, each containing coherently moving dots. The observers' task was to estimate the direction of motion of the dots in the central region. By itself, motion in either annulus can alter this estimate, producing a contrast effect whereby the perceived direction of the center is biased away from the direction of motion of the annulus. In combination, the outer annulus dominated the inner in its effect on the target's motion. This result suggests that local operators, such as antagonistic center-surround mechanisms for motion direction, are in themselves insufficient to explain relative motion effects.

2. Brightness Perception [Article 8]

A neural network model is developed to explain how visual thalamocortical interactions give rise to boundary percepts such as illusory contours and surface percepts such as filled-in brightnesses. Top-down feedback interactions are needed in addition to bottom-up feedforward interactions to simulate these data. One feedback loop is modeled between lateral geniculate nucleus (LGN) and cortical area V1, and another within cortical areas V1 and V2. The first feedback loop realizes a matching process which enhances LGN cell activities that are consistent with those of active cortical cells, and suppresses LGN activities that are not. This corticogeniculate feedback, being endstopped and oriented, also enhances LGN ON cell activations at the ends of thin dark lines, thereby leading to enhanced cortical brightness percepts when the lines group into closed illusory contours. The second feedback loop generates boundary representations, including illusory contours, that coherently bind distributed cortical features together. Brightness percepts form within the surface representations through a diffusive filling-in process that is contained by resistive gating signals from the boundary representations. The model is used to simulate illusory contours and surface brightnesses induced by Ehrenstein disks, Kanizsa squares, Glass patterns, and café wall patterns in single contrast, reverse contrast, and mixed contrast configurations. These examples illustrate how boundary and surface mechanisms can generate percepts that are highly context-sensitive, including how illusory contours can be amodally recognized without being seen, how model simple cells in V1 respond preferentially to luminance discontinuities using inputs from both LGN ON and OFF cells, how model bipole cells in V2 with two colinear receptive fields can help to complete curved illusory contours, how short-range simple cell groupings and long-range bipole cell groupings can sometimes generate different outcomes, and how model double opponent, filling-in and boundary segmentation mechanisms in V4 interact to generate surface brightness percepts in which filling-in of enhanced brightness and darkness can occur before the net brightness distribution is computed by double opponent interactions.

3. Spatial Pooling and Perceptual Framing by Synchronized Cortical Dynamics [Article 12]

How does the brain group together different parts of an object into a coherent visual object representation? Different parts of an object may be processed by the brain at dif-

ferent rates and may thus become desynchronized. Perceptual framing is a process that resynchronizes cortical activities corresponding to the same retinal object. A neural network model is presented that is able to rapidly resynchronize desynchronized neural activities. The model provides a link between perceptual and brain data. Model properties quantitatively simulate perceptual framing data, including psychophysical data about temporal order judgments and the reduction of threshold contrast as a function of stimulus length. Such a model has earlier been used to explain data about illusory contour formation, texture segregation, shape-from-shading, 3-D vision, and cortical receptive fields. The model hereby shows how many data may be understood as manifestations of a cortical grouping process that can rapidly resynchronize image parts which belong together in visual object representations. The model exhibits better synchronization in the presence of noise than without noise, a type of stochastic resonance, and synchronizes robustly when cells that represent different stimulus orientations compete. These properties arise when fast long-range cooperation and slow short-range competition interact via nonlinear feedback interactions with cells that obey shunting equations.

4. Binocular Disparity Processing [Article 11]

A neural model of binocular vision is developed to simulate psychophysical and neurobiological data concerning the dynamics of binocular disparity processing. The model shows how feedforward and feedback interactions among LGN ON and OFF cells and cortical simple, complex, and hypercomplex cells can simulate binocular summation, the Pulfrich effect, and the fusion of delayed anticorrelated stereograms. Model retinal ON and OFF cells are linked by an opponent process capable of generating antagonistic rebounds from OFF cells after offset of an ON cell input. Spatially displaced ON and OFF cells excite simple cells. Opposite polarity simple cells compete before their half-wave rectified outputs excite complex cells. Complex cells binocularly match like-polarity simple cell outputs before pooling half-wave rectified signals from opposite polarities. Competitive feedback among complex cells leads to sharpening of disparity selectivity and normalizes cell activity. Slow inhibitory interneurons help to reset complex cells after input offset. The Pulfrich effect occurs because the delayed input from the one eye fuses with the present input from the other eye to create a disparity. Binocular summation occurs for stimuli of brief duration or of low contrast because competitive normalization takes time. and cannot occur for very brief or weak stimuli. At brief SOAs, anticorrelated stereograms can be fused because the rebound mechanism ensures that the present image to one eye can fuse with the afterimage from a previous image to the other eye. Corticogeniculate feedback embodies a matching process that enhances the speed and temporal accuracy of complex cell disparity tuning. Model mechanisms interact to control the stable development of sharp disparity tuning.

5. Synthetic Aperture Radar Processing by a Multiple Scale Neural System for Boundary and Surface Representation [Article 16]

An algorithm based on an improved Boundary Contour System (BCS) and Feature Contour System (FCS) neural network vision model is developed to process images containing range data gathered by synthetic aperture radar (SAR) sensor. BCS/FCS processing makes structures such as motor vehicles, roads, and buildings more salient and interpretable to human observers than they are in the original imagery. Early processing by ON cells and OFF cells embedded in shunting center-surround networks normalizes input dynamic range

and performs local contrast enhancement. Combining ON cell and OFF cell output in the BCS to define oriented filters overcomes complementary processing deficiencies of each cell type and improves sensitivity to image contours. The oriented filters output to stages of short-range competition and long-range cooperation that segment the image into regions by cooperatively completing and regularizing the most favored boundaries while suppressing image noise and weaker boundary groupings. Boundary segmentation is performed by three copies of the BCS at small, medium, and large scales, whose interaction distances covary with the size of the scale. Filling-in of surface representations occurs within the FCS at each scale via a diffusion process. Diffusion is activated by the normalized FCS inputs and restricted to the compartments defined within each BCS boundary segmentation. The three scales of surface representation are then added to yield a final multiple-scale output.

6. Perception of Lightness [Article 24]

Lightness constancy requires the visual system to somehow "parse" the input scene into illumination and reflectance components. Experiments on the perception of lightness for 3-D curved objects show that human observers are able to perform such a decomposition for some scenes but not for others. Lightness constancy is quite good when a rich local gray level context is provided. Deviations occurr when both illumination and reflectance changed along the surface of the objects. Does the perception of a 3-D surface and illuminant layout help calibrate lightness judgments? Results show a small but consistent improvement between lightness matches on ellipsoid shapes compared to flat rectangle shapes under similar illumination conditions. Illumination change over 3-D forms is therefore taken into account in lightness perception.

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Clark Dorman, Alexander Grunewald, Michelle Hampson, Gregory Lesher, Scott Oddo, Christopher Pack, David Pedini, Luiz Pessoa, Doron Tal, James Williamson, and Jeff Yuan—graduate students in the Department of Cognitive and Neural Systems—received partial support during the three years of the grant.

Grunewald received his PhD degree in Cognitive and Neural Systems in May, 1995. The topic of his dissertation was "Temporal dynamics of visual processing". He is currently working at the California Institute of Technology.

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Pessoa received his PhD degree in Cognitive and Neural Systems in January 1996. The topic of his dissertation was "Studies of human vision: A neural network model of brightness perception and experiments on chromatic textures". He is currently working as a research assistant at the Federal University of Rio de Janeiro, Brazil.

Williamson received his PhD degree in Cognitive and Neural Systems in January 1996. The topic of his dissertation was "Neural networks for image processing, classification, and understanding". He is currently working as a postdoctoral fellow in the CNS Department at Boston University.

Dorman, Hampson, Oddo, Pack, Tal, and Yuan continue to work towards the completion of a PhD degree.

APPENDIX A

YEAR 1 RESEARCH SUMMARIES

1. Multichannel Data Fusion by a Self-Organizing Network for Recognition and Prediction

Fusion ARTMAP is a self-organizing neural network architecture for multi-channel, or multi-sensor, data fusion. Single-channel Fusion ARTMAP is functionally equivalent to Fuzzy ART during unsupervised learning and to Fuzzy ARTMAP during supervised learning. The network has a symmetric organization such that each channel can be dynamically configured to serve as either a data input or a teaching input to the system. An ART module forms a compressed recognition code within each channel. These codes, in turn, become inputs to a single ART system that organizes the global recognition code. When a predictive error occurs, a process called parallel match tracking simultaneously raises vigilances in multiple ART modules until reset is triggered in one of them. Parallel match tracking hereby resets only that portion of the recognition code with the poorest match, or minimum predictive confidence. This internally controlled selective reset process is a type of credit assignment that creates a parsimoniously connected learned network. Fusion ARTMAP's multi-channel coding is illustrated by simulations of the Quadruped Mammal database.

2. Object Recognition and Image Understanding

The What-and-Where filter forms part of a neural network architecture for spatial mapping, object recognition, and image understanding. The Where filter responds to an image figure that has been separated from its background. It generates a spatial map whose cell activations simultaneously represent the position, orientation, and size of the figure (where it is). This spatial map may be used to direct spatially localized attention to these image features. A multiscale array of oriented detectors, followed by competitive interactions between position, orientation, and size scales, is used to define the Where filter. The Where filter may be used to transform the image figure into an invariant representation that is insensitive to the figure's original position, orientation, and size. This invariant figural representation forms part of a system devoted to attentive object learning and recognition (what it is). The Where spatial map of all the figures in an image, taken together with the invariant recognition categories that identify these figures, can be used to learn multidimensional representations of objects and their spatial relationships for purposes of image understanding. The What-and-Where filter is inspired by neurobiological data showing that a Where processing stream in the cerebral cortex is used for attentive spatial localization and orientation, whereas a What processing stream is used for attentive object learning and recognition.

3. Processing of Synthetic Aperture Radar Images by a Multiscale Boundary Segmentation and Surface Representation Architecture

A multiscale image processing algorithm based on the Boundary Contour System (BCS) and Feature Contour System (FCS) neural network models of preattentive vision, developed at Boston University's Center for Adaptive Systems and Department of Cognitive and Neural Systems, has been transferred to MIT's Lincoln Laboratory and applied to large images containing range data gathered by a synthetic aperture radar (SAR) sensor. Researchers at

Lincoln Laboratory have in turn supplied enhanced versions of that software to clients at other laboratories. The goal of the algorithm is to make structures such as motor vehicles, roads, or buildings more salient and more interpretable to human observers than they are in the original imagery. Early automatic gain control by shunting center-surround networks compresses signal dynamic range while performing local contrast enhancement. Subsequent processing by filters sensitive to oriented contrast, including short-range competition and long-range cooperation, segments the image into regions. The segmentation is performed by three "copies" of the BCS and FCS, of small, medium, and large scales, wherein the "short-range" and "long-range" interactions within each scale occur over smaller or larger image distances, corresponding to the size of the early filters of each scale. Finally, a diffusive filling-in operation within the segmented regions generates surface representations of visible structures. The combination of BCS and FCS helps to locate and enhance structure over regions of many pixels, without the resulting blur characteristic of approaches based on low spatial frequency filtering alone.

4. Dynamic Reset of Boundary Segmentations in Response to Rapidly Changing Imagery

An analysis of the reset of visual cortical circuits responsible for the binding or segmentation of visual features into coherent visual forms yielded a model that explains properties of visual persistence described in Francis, Grossberg, and Mingolla (in press). The reset mechanisms prevent massive smearing of visual percepts in response to rapidly moving images. The model simulates relationships among psychophysical data showing inverse relations of persistence to flash luminance and duration, greater persistence of illusory contours than real contours, a U-shaped temporal function for persistence of illusory contours, a reduction of persistence due to adaptation with a stimulus of like orientation, an increase of persistence due to adaptation with a stimulus of perpendicular orientation, and an increase of persistence with spatial separation of a masking stimulus. The model suggests that a combination of habituative, opponent, and endstopping mechanisms prevent smearing and limit persistence.

The model consists of the BCS with habituative chemical transmitters embedded at the interface of its complex cells and hypercomplex cells. Thus *all* the properties used in image processing applications of the BCS are retained in the present model, which provides the additional advantage of rapidly resetting *only* those boundary groupings of a processed scene which are *changing* in a time-varying environment.

5. A Network Architecture to Rapidly Search and Detect Visual Targets in Clutter

Visual search data were given a unified quantitative explanation by a model of how spatial maps in the parietal cortex and object recognition categories in the inferotemporal cortex deploy attentional resources as they reciprocally interact with visual representations in the prestriate cortex, as described in Grossberg, Mingolla, and Ross (in press). The model visual representations are organized into multiple boundary and surface representations. Visual search in the model is initiated by organizing multiple items that lie within a given boundary or surface representation into a candidate search grouping. These items are compared with object recognition categories to test for matches or mismatches. Mismatches can trigger deeper searches and recursive selection of new groupings until a target object is

identified. This search model is algorithmically specified to quantitatively simulate search data using a single set of parameters, as well as to qualitatively explain a still larger data base, including data of Aks and Enns (1992), Bravo and Blake (1990), Chellazzi, Miller, Duncan, and Desimone (1993), Cohen and Ivry (1991), Egeth, Virzi, and Garbart (1984), Enns and Rensink (1990), He and Nakayama (1992), Humphreys, Quinlan, and Riddoch (1989), Mordkoff, Yantis, and Egeth (1990), Nakayama and Silverman (1986), Treisman and Gelade (1980), Treisman and Sato (1990), Wolfe, Cave, and Franzel (1989), and Wolfe and Friedman-Hill (1992). The model hereby provides an alternative to recent variations on the Feature Integration and Guided Search models, and grounds the analysis of visual search in neural models of preattentive vision, attentive object learning and categorization, and attentive spatial localization and orientation.

6. Human Psychophysical Experiments on Boundary Segmentation

Lesher and Mingolla (1993) showed that illusory contours can be induced along directions approximately collinear to edges or approximately perpendicular to the ends of lines. Using a rating scale procedure, they explored the relation between the two types of inducers by systematically varying the thickness of inducing elements to result in varying amounts of "edge-like" or "line-like" induction. Inducers for the illusory figures consisted of concentric rings with arcs missing. Observers judged the clarity and brightness of illusory figures as the number of arcs, their thicknesses, and spacing were parametrically varied. Degree of clarity and amount of induced brightness were both found to be inverted-U functions of the number of arcs. These results mandate that any valid model of illusory contour formation must account for interference effects between parallel lines or between those neural units responsible for completion of boundary signals in directions perpendicular to the ends of thin lines. Line width was found to have an effect on both clarity and brightness, a finding inconsistent with those models which employ *only* completion perpendicular to inducer orientation. Subsequent research reported in Lesher (1993) showed that the BCS could fit the data of the Lesher and Mingolla (1993) experiment.

7. A Link between Brightness Perception, Illusory Contours, and Binocular Corticogeniculate Feedback

As reported in Gove, Grossberg. and Mingolla (1994), many illusory contour displays induce apparent brightness along the ends of thin lines. "Brightness buttons" are usually described as unnoticed for sinlge lines, but effective in producing the enhanced brightness inside the illusory contours induced by Ehrenstein patterns. No satisfactory neural mechanism for brightness buttons has yet been suggested. We propose that they are consequences of corticogeniculate feedback whose primary functional role is to selectively prime monocular LGN cells whose activation is consistent with fused binocular activation of cortical V1 cells. We simulated a model of neural circuitry of LGN and V1. Model LGN relay cells receive input from retinal cells, positive feedback from oriented V1 cells, and negative feedback from LGN interneurons, which also receive cortical feedback. Brightness button signals can be generated in two ways consistent with reported physiology: (1) Excitatory feedback from cortical end-stopped cells can enhance LGN cell activity near line ends; (2) Net inhibitory feedback from long-field cells, modulated by LGN interneurons, can suppress activity in LGN cells coding the sides of lines, making brightness contrast at line ends relatively stronger. A combination of the two mechanisms has the same properties. Our research shows that

brightness enhancement of illusory figures that are induced at line ends may reflect corticogeniculate feedback mechanisms. These mechanisms select monocular LGN cells whose activation is consistent with that of the binocular cortical cells that are used to form the illusory contours.

8. Relation of Hyperacuity and Illusory Contour Data

Lesher's (1993) dissertation contains (among other projects) simulations describing how the BCS can fit the illusory contour data of Project 6 in a manner that unifies the treatment of hyperacuity data and illusory contour formation, as first described by Grossberg (1987). Tradeoffs in network design for optimal spatial resolution and for reconciling long-range contextual information with local data are thereby accorded a unified treatment.

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APPENDIX B

YEAR 2 RESEARCH SUMMARIES

1. Spatial Pooling and Perceptual Framing by Synchronized Cortical Dynamics

How does the brain group together different parts of an object into a coherent visual object representation? Different parts of an object may be processed by the brain at different rates and may thus become desynchronized. Perceptual framing is a process that resynchronizes cortical activities corresponding to the same retinal object. A neural network model was developed that is able to rapidly resynchronize desynchronized neural activities. Model properties quantitatively simulate perceptual framing data, including psychophysical data about temporal order judgments and the reduction of threshold contrast as a function of stimulus length. The model also exhibits better synchronization in the presence of noise than without noise, a type of stochastic resonance, and synchronizes robustly when cells that represent different stimulus orientations compete. The model utilizes fast long-range cooperative feedback that interacts with slow competitive feedback from inhibitory interneurons. Such a model has earlier been used to explain data about illusory contour formation, texture segregation, shape-from-shading, 3-D vision, and cortical receptive fields. The model hereby shows how all these data may be understood as manifestations of a cortical process that can rapidly resynchronize image parts which belong together in visual object representations.

2. Synthetic Aperture Radar Processing by a Multiple Scale Neural System for Boundary and Surface Representation

An algorithm based on an improved Boundary Contour System (BCS) and Feature Contour System (FCS) neural network vision model is developed to process images containing range data gathered by synthetic aperture radar (SAR) sensor. BCS/FCS processing makes structures such as motor vehicles, roads, and buildings more salient and interpretable to human observers than they are in the original imagery. Early processing by ON cells and OFF cells embedded in shunting center-surround networks normalizes input dynamic range and performs local contrast enhancement. Combining ON cell and OFF cell output in the BCS to define oriented filters overcomes complementary processing deficiencies of each cell type and improves sensitivity to image contours. The oriented filters output to stages of short-range competition and long-range cooperation that segment the image into regions by cooperatively completing and regularizing the most favored boundaries while suppressing image noise and weaker boundary groupings. Boundary segmentation is performed by three copies of the BCS at small, medium, and large scales, whose interaction distances covary with the size of the scale. Filling-in of surface representations occurs within the FCS at each scale via a diffusion process. Diffusion is activated by the normalized FCS inputs and restricted to the compartments defined within each BCS boundary segmentation. The three scales of surface representation are then added to yield a final multiple-scale output.

3. Formation of Cortical Maps of Ocular Dominance and Orientation Columns

Three computational rules are sufficient to generate model cortical maps that simulate the interrelated structure of cortical ocular dominance and orientation columns: a noise input, a spatial band pass filter, and competitive normalization across all feature dimensions.

The data of Blasdel from optical imaging experiments reveal cortical map fractures, singularities, and linear zones that are fit by the model. In partiuclar, singularities in orientation preference tend to occur in the centers of ocular dominance columns, and orientation contours tend to intersect ocular dominance columns at right angles. The model embodies a universal computational substrate that all models of cortical map development and adult function need to realize in some form.

4. A Neuron Model with Variable Ion Concentrations

Voltage is the central focus of most models of the single neuron. Recently interest in long-term potentiation (LTP) has surged, due to its linked to learning. It has been shown that LTP is accompanied by an increase of the internal calcium concentration. Prior models have included provision for variable calcium concentrations, but since the calcium concentration in these models is typically very low, it has a negligible effect on the membrane potential. In the present model all ion concentrations are variable due to ionic current and due to ion pumps. It is shown that this significantly increases the complexity of neural processing, and thus variable ion concentrations cannot be ignored in neurons with high firing frequency, or with very long depolarizations.

5. A Multi-Scale Network Model of Brightness Perception

A model is developed to account for a wide variety of difficult data, including the classical phenomenon of Mach bands, low- and high-contrast missing fundamental and nonlinear contrast effects associated with sinusoidal luminance waves. The model builds upon previous work by Grossberg and colleagues on filling-in models that predict brightness perception through the interaction of *boundary* and *feature* signals. Simulations of the model implement a number of refinements already described in the development of Grossberg's (1987, 1994) Form-And-Color-And-DEpth (FACADE) theory, which though conceived as part of the theory, were not implemented in the simulations of Grossberg and Todorović (1988). These include: (a) ON and OFF channels with separate filling-in domains; (b) multiple spatial scales; (c) revised computations for simple and complex cells; and (d) boundary computations that engage a recurrent competitive circuit. Simulations of the present system of equations account for human's perception of a wide variety of stimuli, including ones whose brightness contains shallow spatial gradients.

6. Models of Motion Perception

This encyclopedia article reviews the major historical data on human visual motion perception and describes classical attempts to model motion detection. It then describes recent developments in a more comprehensive model, called the Motion Boundary Contour System, proposed by Grossberg and colleagues.